

1 **Smartphone-based heart rate variability biofeedback training improves premenstrual**  
2 **and depressive symptoms as well as anxiety/stress symptoms and attentional**  
3 **executive control: a pilot study**

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16 Running head: Smartphone-based Heart Rate Variability Biofeedback for PMS

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18 **Keywords: smartphone photoplethysmography, mHealth, heart rate variability,**  
19 **biofeedback, vagal tone, premenstrual syndrome, premenstrual symptoms, menstrual**  
20 **cycle, stress, depression, attentional control**

21 Scope Statement (for Frontiers in Public Health):

22 Heart rate variability biofeedback (HRVB) is a well-researched intervention with documented  
23 positive effects on mental health and cognitive outcomes. However, its practical  
24 implementation is hindered by the high costs associated with obtaining stationary and mobile  
25 ECG devices and the need for trained personnel. Recent advances in smartphone-based  
26 biofeedback offer a promising avenue to achieve similar outcomes. Yet, existing studies often  
27 rely on external devices for heart rate measurement. In our study, we assess a smartphone-  
28 based HRVB app, using photoplethysmography via the integrated camera as measurement  
29 method, making it cost-effective and widely accessible.

30 Premenstrual symptoms affect up to 90% of individuals with an active menstrual cycle, with  
31 research predominantly focusing on pharmacological treatments with significant side effects.  
32 HRVB provides a low-threshold self-management method for these symptoms, which has not  
33 been tested in this context. Our research reveals the beneficial effects of smartphone-based  
34 HRVB training on premenstrual and depressive symptoms as well as anxiety/stress symptoms  
35 and executive attentional control.

36 Our study is of interest to Frontiers in Public Health readers as it introduces a digital solution  
37 to enhance mental health outcomes, which makes this intervention more accessible to the  
38 public. By promoting resilience, it can help to prevent symptom chronification and clinical  
39 escalation, benefiting individuals and healthcare systems.

1 **Abstract**

2 **Introduction**

3 Heart rate variability biofeedback (HRVB) is a well-studied intervention known for its  
4 positive effects on emotional, cognitive, and physiological well-being, including relief from  
5 depressive symptoms. However, its practical use is hampered by high costs and a lack of  
6 trained professionals. Smartphone-based HRVB, which eliminates the need for external  
7 devices, offers a promising alternative, albeit with limited research. Additionally,  
8 premenstrual symptoms are highly prevalent among menstruating individuals, and there is a  
9 need for low-cost, accessible interventions with minimal side effects. With this pilot study,  
10 we aim test, for the first time, the influence of smartphone-based HRVB on depressive and  
11 premenstrual symptoms, as well as anxiety/stress symptoms and attentional control.

12 **Methods**

13 Twenty-seven participants with above-average premenstrual or depressive symptoms  
14 underwent a 4-week photoplethysmography smartphone-based HRVB intervention using a  
15 waitlist-control design. Laboratory sessions were conducted before and after the intervention,  
16 spaced exactly 4 weeks apart. Assessments included resting vagally mediated heart rate  
17 variability (vmHRV), attentional control via the revised attention network test (ANT-R),  
18 depressive symptoms assessed with the BDI-II questionnaire, and stress/anxiety symptoms  
19 measured using the DASS questionnaire. Premenstrual symptomatology was recorded  
20 through the PAF questionnaire if applicable. Data analysis employed linear mixed models.

21 **Results**

22 We observed improvements in premenstrual, depressive, and anxiety/stress symptoms, as  
23 well as the Executive Functioning Score of the ANT-R during the intervention period but not  
24 during the waitlist phase. However, we did not find significant changes in vmHRV or the  
25 Orienting Score of the ANT-R.

26 **Discussion**

27 These findings are promising, both in terms of the effectiveness of smartphone-based HRVB  
28 and its potential to alleviate premenstrual symptoms. Nevertheless, to provide a solid  
29 recommendation regarding the use of HRVB for improving premenstrual symptoms, further  
30 research with a larger sample size is needed to replicate these effects.

31

# 1 1 Introduction

2 Heart rate variability biofeedback (HRVB) is a well-researched intervention that has  
3 demonstrated effectiveness in a wide range of areas (Lehrer et al., 2020), including relieving  
4 anxiety and stress (Goessl et al., 2017), ameliorating depression (Pizzoli et al., 2021),  
5 improving sleep (Stein & Pu, 2012), alleviating asthma symptoms (Lehrer et al., 2004), and  
6 even enhancing sports performance (Jiménez Morgan & Molina Mora, 2017). However,  
7 despite its potential, this user-friendly method has seen limited practical implementation. This  
8 can be attributed, in part, to the high costs associated with necessary stationary and mobile  
9 electrocardiography (ECG) devices, as well as the required training and expertise of staff  
10 members entrusted with its administration, which further strains healthcare systems.  
11 Encouragingly, smartphone apps capable of assessing heart rate through the device's camera,  
12 without additional equipment, are promising to yield similar results (Yuda et al., 2020).  
13 Nevertheless, empirical validation of smartphone-based HRVB applications remains limited.  
14 This study aims to validate the effectiveness of an HRVB intervention applied through  
15 smartphones, specifically targeting the alleviation of depressive symptoms, a well-  
16 documented outcome of conventional HRVB. Additionally, we explore a novel application of  
17 HRVB for premenstrual symptoms.

18 HRVB is a method in which vagally mediated heart rate variability (vmHRV), an indicator of  
19 parasympathetic activity (Laborde et al., 2023; Penttilä et al., 2001), is systematically  
20 increased through slow, controlled breathing and visual feedback of heart rate oscillations.  
21 The primary driving mechanism involves slow-paced breathing at 0.1 Hz or an individual  
22 resonance frequency (Laborde, Allen, Borges, Iskra, et al., 2022). It is believed to exert its  
23 various beneficial effects through bottom-up modulation of a neural network described by  
24 Thayer and Lane (2000) in their neurovisceral integration model.

25 This model delineates a network of interconnected structures known as the central autonomic  
26 network (CAN), responsible for integrating information and regulating appropriate responses.  
27 At the core of this regulatory network, Thayer and Lane (2009) propose an inhibitory  
28 connectivity between the medial prefrontal cortex (mPFC) and the amygdala. The stronger  
29 this connectivity, the greater an individual's capacity to downregulate a presumed default  
30 stress response and deliver a precise and personalized reaction to internal and environmental  
31 demands. VmHRV is considered both a peripheral index for this capacity and a reciprocal  
32 element within this network (Thayer et al., 2009). This theory is grounded in a substantial  
33 body of evidence linking low vmHRV to psychopathology (Heiss et al., 2021) and reduced  
34 performance in cognitive self-control tasks (Holzman & Bridgett, 2017; Zahn et al., 2016).

35 When practiced over several weeks, HRVB enhances the capacity of the CAN through  
36 coherence phenomena involving the synchronization of breathing rate, blood pressure, and  
37 heart rate oscillations (Sevoz-Couche & Laborde, 2022). These phenomena contribute to  
38 several bottom-up routes. The most crucial of these routes involve input into the CAN  
39 through baroreceptors via the nucleus of the solitary tract, stretch receptors in the lungs, and a  
40 vagal afferent pathway (Lehrer & Gevirtz, 2014; Noble & Hochman, 2019; Sevoz-Couche &  
41 Laborde, 2022).

42 HRVB interventions have demonstrated the potential to improve various affective and  
43 cognitive outcomes associated with CAN capacity, including depression (Pizzoli et al., 2021)  
44 and anxiety (Goessl et al., 2017). Our study aims to expand these effects in the context of a

1 smartphone-based intervention. While vmHRV is reliably associated with cognitive  
2 outcomes, particularly executive functions, the impact of HRVB on these variables is less  
3 clear (Tinello et al., 2022). In a systematic review, Tinello et al. (2022) found that existing  
4 effects are primarily observed in the domain of attentional control and are often found in  
5 patient populations or individuals experiencing high levels of stress. Given that attention is  
6 strongly linked to vmHRV, we also investigate the effect of HRVB on attentional control  
7 using the revised Attention Network Test (ANT-R, Blaser et al., 2023a; Fan et al., 2009).

8 Expanding on these replications, we further investigate HRVBs impact on premenstrual  
9 syndrome (PMS), a highly prevalent condition characterized by a diverse collection of  
10 psychological and physiological symptoms. These symptoms typically manifest in  
11 individuals with active menstrual cycles during the week leading up to menstruation and tend  
12 to subside shortly after. As many as 90% of menstruating individuals regularly encounter at  
13 least one symptom of PMS (Tschudin et al., 2010). Commonly reported symptoms  
14 encompass heightened stress reactivity, anxiety, depressive mood, breast tenderness, and  
15 abdominal pain (Allen et al., 1991).

16 As a component of the gender data gap, premenstrual syndrome (PMS) remains significantly  
17 under-researched (Zehravi et al., 2023). Even today, treatment options remain limited,  
18 primarily centered on addressing specific psychological or physiological symptoms through  
19 hormonal cycle suppression or antidepressant medication in both clinical practice and  
20 research (Ryu & Kim, 2015). Both of these approaches are associated with substantial  
21 adverse side effects (Price et al., 2009; Robinson et al., 2004; Skovlund et al., 2016).

22 Premenstrual symptoms have been linked to cyclic fluctuations in vagally mediated heart rate  
23 variability (vmHRV) (Schmalenberger et al., 2019). Individuals who experience more severe  
24 symptoms tend to exhibit a pronounced reduction in vmHRV during the luteal phase of their  
25 menstrual cycle, coinciding with the experience of these symptoms (Matsumoto et al., 2007).  
26 Matsumoto et al. (2007) have suggested a potential causal relationship in this regard.

27 One possible explanation for this phenomenon lies in a metabolite of progesterone, one of the  
28 main fluctuating gonadal steroids during the menstrual cycle. Sundström-Poromaa et al.  
29 (2003) have identified this metabolite, namely Allopregnanolone (ALLO), an allosteric  
30 Gamma-Aminobutyric Acid (GABA) receptor modulator as a likely cause of the experience  
31 of premenstrual symptoms (Hantsoo & Epperson, 2020). As ALLO operates on the  
32 GABAergic system, the proposed CAN in the neurovisceral integration theory (Thayer &  
33 Lane, 2000, 2009) might also be affected. In this theory, successful adaptation relies on  
34 inhibitory connectivity between the mPFC and the amygdala. The strength of these  
35 connections, which are part of the central nervous system's inhibitory GABAergic network,  
36 are influenced by GABA levels in the mPFC (Delli Pizzi et al., 2017). Compromised  
37 inhibition in this circuit due to ALLO withdrawal and/or maladaptive ALLO responses may  
38 lead to a compromised self-regulatory capacity of the organism on both affective and  
39 physiological levels, as observed in PMS.

40 Following this line of reasoning, HRVB is a promising candidate to counteract some of these  
41 effects through two mechanisms. Firstly, the most pronounced effects of HRVB are observed  
42 in stress management (Goessl et al., 2017). If stress throughout the cycle causes irregularities  
43 in the ALLO system during the premenstrual phase, reducing stress throughout the cycle may  
44 prevent some of the symptom development. Existing evidence already suggests that various

1 relaxation techniques can positively impact PMS (Jose et al., 2022). Secondly, HRVB is  
2 assumed to increase the inhibitory capacity of the mPFC over the amygdala and, as a result,  
3 enhance the inhibition of the default stress response (Schumann et al., 2021). Although  
4 GABAergic transmission may be compromised during the premenstrual phase, boosting the  
5 baseline inhibitory strength between these two brain structures could raise inhibition levels.  
6 This might make it less likely for a sudden drop to cross the threshold to trigger symptoms  
7 that cause significant distress.

8 Initial studies have already provided evidence of the effectiveness of HRVB for mental health  
9 outcomes when administered through smartphones. Previous studies that utilized smartphone-  
10 based HRVB interventions to improve outcomes like depressive or anxiety symptoms,  
11 however, have typically relied on external devices connected to the smartphone via  
12 Bluetooth. These devices include wearable ECG-measuring breast straps (Chung et al., 2021;  
13 Herhaus et al., 2022; Lin, 2018; Schumann et al., 2022; Schumann et al., 2021) or earlobe-  
14 clip pulse measuring devices (Economides et al., 2020; Minen et al., 2021; Schuman et al.,  
15 2023). Acquiring a wearable device presents a significant obstacle for potential HRVB users.

16 Smartphone cameras can now measure heart rate when the user places a finger on the camera.  
17 An application activates the camera flash and analyzes the red-to-green ratio in the image at  
18 high frequency, generating pulse curves. This process is known as photoplethysmography  
19 (PPG) and closely resembles the process behind the optical sensors that emit infrared or green  
20 light in commonly used pulse measurement devices. Yuda et al. (2020) suggest that the heart  
21 rate variability indicator used in smartphone apps, which they term 'pulse rate variability' as  
22 measured through PPG, may contain distinct information compared to its ECG-measured  
23 counterpart. Nevertheless, recent research has demonstrated very high correlations between  
24 HRV parameters measured through ECG and PPG of over .9 (van Dijk et al., 2023), even  
25 though the reliability is somewhat dependent on sampling rate of the device (Guede-  
26 Fernández et al., 2020). Moreover, the associations with mental health outcomes are also  
27 evident when assessing vmHRV via PPG using the smartphone camera (Liu et al., 2020).  
28 This supports the use of PPG as a foundation for HRVB.

29 In this study, we investigated the novel application of a 4-week smartphone-based HRVB  
30 intervention using PPG via smartphone camera instead of an external device for alleviating  
31 depressive and premenstrual symptoms. Our sample comprised young adults who either  
32 exhibited above-average PMS or depressive symptoms. Additionally, we examined the  
33 impact of the intervention on various other outcomes, including anxiety and stress symptoms,  
34 attentional control, and vmHRV.

## 35 **2 Methods**

### 36 **2.1 Participants**

37 A G\*Power analysis revealed that a sample size of 40 was necessary to detect an effect size  
38 of .4, based on a meta-analytic effect of HRVBFB on depressive symptoms reported by  
39 Pizzoli et al. (2021), with a power of .8 and a one-tailed alpha error probability of .05.  
40 However, due to recruitment difficulties and resourcing issues by the company providing the  
41 app during the extended recruitment period, we were unable to reach our target of 40  
42 participants.

1 Twenty-nine participants were recruited from the student population of the University of  
2 Potsdam for this study. Recruitment was carried out via the online recruiting platform for  
3 study participants of the cognitive sciences (Sona Systems, <https://www.sona-systems.com>)  
4 of University Potsdam as well as via flyers on campus and advertisement in university  
5 mailing lists. Inclusion criteria required participants to have either above-average  
6 premenstrual symptomatology (short version Premenstrual Assessment Form, PAF20  $\geq$  50),  
7 depressive symptoms that indicate at least minimal depression (Beck's Depression Inventory,  
8 BDI-II  $\geq$  9), or both. Participants who exceeded a BDI-II score of 14 received a consultation  
9 with a clinical psychologist to discuss possible necessary treatment prior to study  
10 participation.

11 Exclusion criteria included factors proposed by Laborde et al. (2017) such as pregnancy,  
12 heart rate-altering chronic diseases or medication. We additionally excluded competitive  
13 athletes to avoid ceiling effects, since this population has systematically increased vmHRV  
14 (Da Silva et al., 2015). Participants currently in any treatment or planning significant lifestyle  
15 changes during the period of study participation were also excluded. In addition, participants  
16 were required to be at least 18 years of age.

17 All participants provided informed consent prior to their inclusion for a study protocol  
18 approved by the ethics committee of the University of Potsdam (No. 30/2022). Participants  
19 who met the inclusion criteria were eligible for study participation and received either course  
20 credits or monetary compensation.

## 21 **2.2 Procedure**

22 The study protocol was preregistered on Open Science Framework ([osf.io/68fzq](https://osf.io/68fzq)). The study  
23 procedure began with an online screening questionnaire to determine eligibility based on  
24 inclusion and exclusion criteria, as well as to assess sociodemographic factors such as age,  
25 gender, study program, and BMI. Participants were also required to provide information  
26 about their menstrual cycle to ensure that the appropriate questionnaires were administered.  
27 Additionally, participants were asked to provide their email address for communication  
28 throughout the study.

29 All eligible participants took part in a 4-week biofeedback intervention during which they  
30 practiced smartphone-based HRVB for at least 5 minutes every day. After the first and  
31 second week, participants additionally received an online coaching session to improve their  
32 technique and address any technical or other difficulty they encountered.

33 Before and after the 4-week intervention, participants completed laboratory sessions that  
34 were scheduled at the same time, exactly 4 weeks apart (T1 and T5). During these sessions,  
35 various measures were collected, including vagally mediated heart rate variability by ECG,  
36 attentional control using the reaction time paradigm ANT-R (Fan et al., 2009), and self-  
37 reported symptoms of depression, premenstrual syndrome (PMS), and anxiety/stress via  
38 questionnaires.

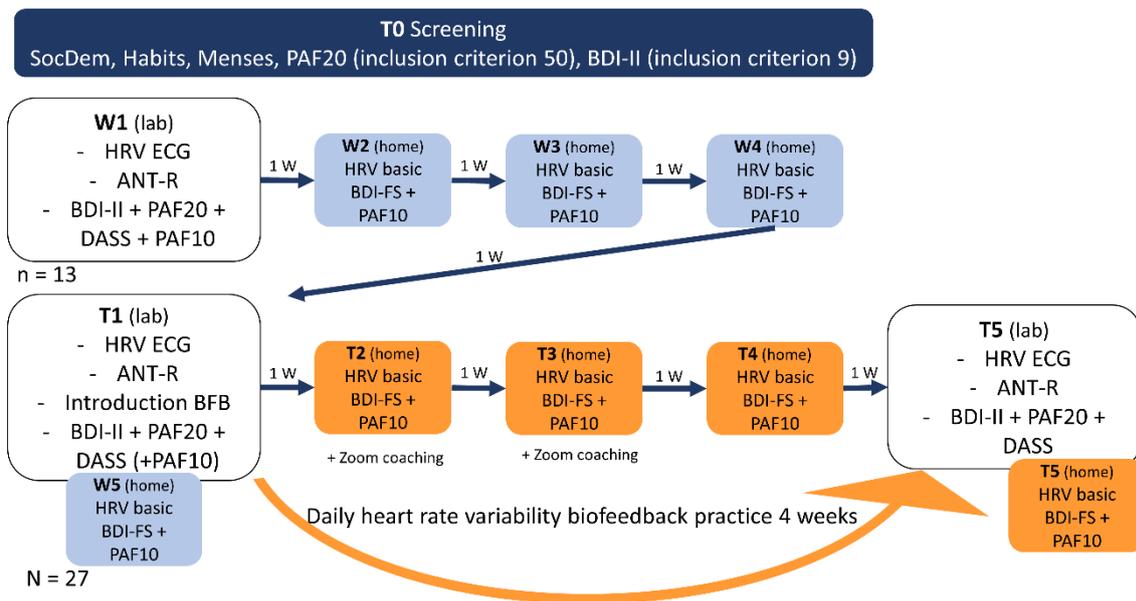
39 To ensure balanced allocation of participants to the waitlist group, half of the participants  
40 within each group of inclusion criteria (depression, PMS, or both) were pseudo-randomly  
41 assigned to the waitlist group. The waitlist group additionally completed a laboratory session  
42 four weeks prior to study inclusion, during which the same parameters were assessed (W1).

1 Throughout the study, participants completed short versions of the depressive and  
 2 premenstrual symptom questionnaires and underwent a photoplethysmography based HRV  
 3 measurement at home using the biofeedback app, each week on the same day and at the same  
 4 time that they chose (W2-W4 and T2-T4). Participants received automated email reminders  
 5 and a link to the respective questionnaire to ensure compliance. The results of these  
 6 measurements are not analysed and reported in this report. Figure 1 provides an overview of  
 7 the study procedure.

8 All participants received an introduction to smartphone-based HRVB during T1. The waitlist  
 9 group received a tutorial on conducting vmHRV measurements at home with the app during  
 10 W1, while the intervention-only group received this tutorial during T1.

11 Since PMS occurs only once during each menstrual cycle, and cycle lengths can vary  
 12 significantly both between and within individuals, we included a follow-up measurement of  
 13 the online questionnaire 4 weeks after T5. If a participant reported no new menstruation onset  
 14 during the last two weeks of the intervention, indicating no new premenstrual phase, we used  
 15 the PMS values reported in the follow-up measurement as the post-intervention values,  
 16 describing the next premenstrual phase after completing the intervention.

17 Figure 1. Study procedure



18

19 Note. SocDem – sociodemographic information, PAF10 – premenstrual assessment form 10  
 20 item version; PAF20 – premenstrual assessment form 20 item version; BDI-II – Beck’s  
 21 Depression Inventory; BDI-FS – Beck’s Depression Inventory short version; ANT-R –  
 22 attention network test-revised; DASS – Depression Anxiety Stress Scale; HRV ECG – heart  
 23 rate variability measurement in lab (electrocardiography); HRV basic – measurement at rest  
 24 at home on phone (photoplethysmography); W – week.

25

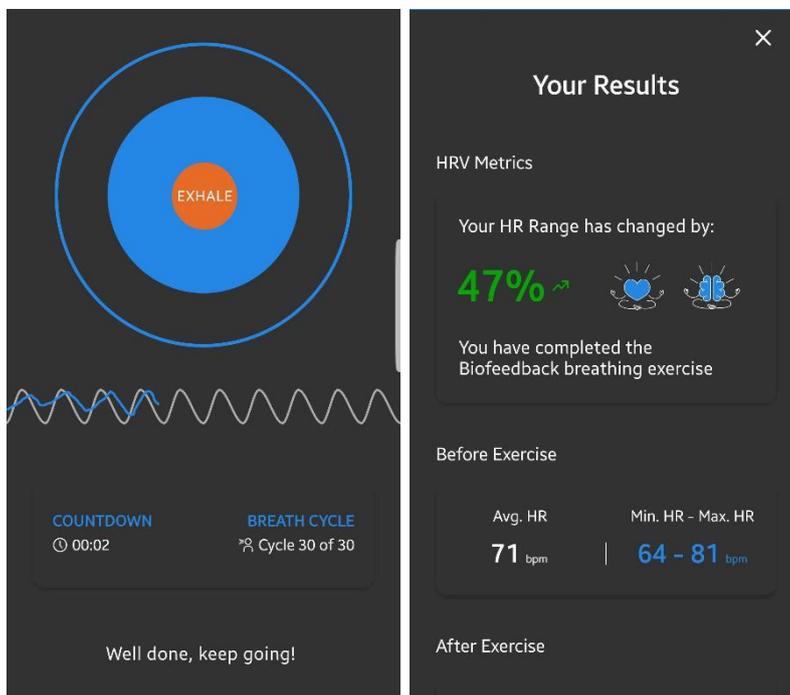
### 2.3 Smartphone-based heart rate variability biofeedback

The HRVB intervention used in this study was app-based and built with the software development kit (SDK) provided by Kenkou GmbH. The app measured HRV via photoplethysmography (PPG), whereby participants placed their index finger on the camera lens and a flash was used to illuminate the tissue. The camera measured the intensity of blood flow, and a peak detection algorithm was used to detect heartbeats.

Before each biofeedback session, participants underwent a 1-minute baseline measurement to assess their current state, which allowed the feedback to be adjusted accordingly. During the biofeedback session, participants saw a growing and shrinking circle indicating the breathing rhythm at 0.1 Hz. A fixed sinus-like wave was also displayed at the frequency of the paced breathing, and the pulse rate over time was mapped on top of this. Participants were instructed that the two waves would converge more as they relaxed. After the HRVB exercise, the user was given feedback on HRV improvement during the exercise to increase motivation. Screenshots of the app can be seen in Figure 2.

15

16 Figure 2. Screenshots of the HRVB application



Note. For the biofeedback, the current respiratory sinus arrhythmia, measured through photoplethysmography using the device's integrated camera, was represented as a blue line. A dynamic expanding and contracting circle visually represented the paced breathing rhythm at a frequency of 0.1 Hz. This frequency was further depicted by gray sinusoidal waves in the background, behind the measured heart rate oscillations.

22

The experimenter provided approximately 15 minutes of instructions to participants on how to use the app and how the biofeedback worked. Participants were coached on how to engage

1 in relaxed slow-paced breathing. They were instructed to practice at least 5 minutes daily for  
2 the next 4 weeks, with the option to practice for longer periods of time if desired. Participants  
3 were also informed that more practice would likely lead to greater benefits.

4 Three participants encountered technical difficulties while running the application on their  
5 devices. To ensure their participation in the intervention, they were provided with an  
6 alternative mobile HRVB system ('Qiu' by Biosign®, D-85570, Ottenhofen, Germany).

## 7 **2.4 Outcome measures**

### 8 **2.4.1 Premenstrual Assessment Form (short form)**

9 The short form of the Premenstrual Assessment Form (PAF20) is a retrospective instrument  
10 that assesses PMS symptoms during the last premenstrual phase (Allen et al., 1991). It was  
11 derived from the 20 most endorsed items of the long form PAF, which includes almost 100  
12 items (Halbreich et al., 1982). Each item represents one premenstrual symptom, for which the  
13 participant must indicate how strongly they experienced it during the last cycle on a 6-point  
14 Likert scale from 1 (not at all/no change) to 6 (extreme change). The German translation of  
15 the PAF-20 shows good internal consistency and reliability and loads on two factors,  
16 indicating a psychological and physiological subscale (Blaser et al., 2023b).

17 The 10-item version (PAF-10) was constructed using the items with the highest factor  
18 loadings and shows a very high correlation with the PAF-20 (Blaser et al., 2023b). To assess  
19 the fluctuations of symptoms throughout the cycle and approximate a prospective assessment,  
20 the participants filled out the PAF-10 once a week with altered instructions, asking for a  
21 report of the 10 symptoms during the last week.

### 22 **2.4.2 Becks Depression Inventory**

23 The Beck Depression Inventory II (BDI-II) is a widely used questionnaire that assesses the  
24 severity of depressive symptoms. It consists of 21 items, each containing four statements  
25 about depressive symptoms ranging from 0 (normal) to 3 (most severe). The total maximum  
26 score is 63. The BDI-II has good psychometric properties, including high internal  
27 consistency, test-retest reliability, and concurrent and discriminant validity. Additionally, the  
28 questionnaire has been translated into multiple languages and is widely used in clinical and  
29 research settings to assess depression severity, monitor treatment progress, and evaluate  
30 outcomes. Previous studies have also shown that the BDI-II has good discrimination between  
31 patients with varying degrees of depression and accurately reflects changes in depression  
32 intensity over time (Beck et al., 1988; Richter et al., 1998).

33 The Fast Screen Version of the Becks Depression Inventory (BDI-FS) was developed as a  
34 short form to allow for parsimonious screenings, e.g., in research settings. It includes seven  
35 items and is based on the DSM-5 criteria for depression, clinical importance, and factor  
36 loadings (Beck et al., 2000).

### 37 **2.4.3 Depression Anxiety Stress Scale**

38 The German version of the Depression Anxiety and Stress Scale (DASS), developed by  
39 Henry and Crawford (2005) and based on the original version by Lovibond and Lovibond  
40 (1995), was employed for data collection. The DASS-21, a shortened version of the scale,  
41 consists of 21 statements that assess three distinct subscales: depression, anxiety, and stress.

1 Participants were asked to rate the extent to which each statement applied to them during the  
2 designated period using Likert scales ranging from 0 to 3. Higher scores on the DASS-21  
3 indicate elevated levels of depressive symptoms, anxiety, and stress.

4 The internal consistency of the DASS-21 was found to be satisfactory, with a Cronbach's  $\alpha$   
5 coefficient of 0.89 (Bibi et al., 2020). The DASS-21 was selected as an outcome measure in  
6 this study based on its consistent effects in biofeedback interventions, as demonstrated in  
7 prior research (Goessl et al., 2017).

#### 8 **2.4.4 Vagally mediated heart rate variability**

9 Resting vmHRV was determined using the BioSign software and hardware ("HRV-Scanner";  
10 Biosign®, D-85570, Ottenhofen, Germany). Participants had been sitting down for at least 15  
11 minutes before the measurement. The measurement was taken in a sitting position.  
12 Participants were instructed to sit comfortably, place their feet side by side on the floor, close  
13 their eyes, and were told that they didn't have to pay attention to anything in particular.  
14 Following the recommendations by Laborde et al. (2017), the measurement had a duration of  
15 5 minutes.

16 HRV was measured by a one-lead electrocardiogram (ECG) through two surface sensors  
17 attached to the right and left wrists of the participant. The device worked with a sampling rate  
18 of 500 Hz and a 16-bit resolution. Artifacts and abnormal beats were filtered in a two-step  
19 process following the software documentation (BioSign GmbH, 2023). First, the HRV  
20 Scanner software automatically marked areas of the heart rate curve that included implausible  
21 changes in heart rate (through the division of the heart rate curve into small segments and a  
22 subsequent scan of each segment). This process was based on an algorithm patented by the  
23 BioSign company that identifies outliers in a Poincaré plot, where each RR interval is plotted  
24 against the previous RR interval.

25 Working with these recognized areas of possible disturbances, in the second step, the R-spike  
26 recognition was manually assessed and corrected, and artifacts (e.g., due to movement) were  
27 removed. After the two-step process, the data quality was excellent, with less than 0.1%  
28 artifacts per measurement on average.

29 Participants additionally conducted short resting vmHRV measurements through the app  
30 using PPG, as described above, once a week. These measurements lasted one minute, and  
31 participants were instructed to take these measurements each week on the same day, at the  
32 same time, and in the same place, ensuring they would not be disturbed. They were also  
33 instructed to sit comfortably and close their eyes during the measurement, similar to the way  
34 they were during the ECG measurement in the laboratory.

35 We used the root mean square of successive differences (RMSSD) as a measure for vagally  
36 mediated heart rate variability. This choice was due to its indication of parasympathetic  
37 output and robustness to influences of breathing rate (Chapleau & Sabharwal, 2011).

#### 38 **2.4.5 Attentional network test revised**

39 We employed the ANT-R, developed by Fan et al. (2009), as a measure of attentional control.  
40 This task is reaction time task and was designed as a combination of the Eriksen flanker task  
41 (Eriksen & Eriksen, 1974) and the Posner cueing task (Posner, 1980).

1 During the ANT-R, participants were presented with a grey background and a black  
2 horizontal arrow. Their task was to indicate the direction of the arrow by pressing the  
3 corresponding button with their left or right index finger.

4 The ANT-R task consists of a total of 288 trials, divided into two identical runs of 144 trials  
5 each. The duration of the entire test is approximately 30 minutes. Previous studies have  
6 demonstrated good split-half reliability in the Executive ( $r = .74$ ) and Orienting network  
7 scores ( $r = .70$ ) (Greene et al., 2008). To reduce participant burden, only one run was  
8 completed per session.

9 The task was administered using the Presentation® software (Neurobehavioral Systems, Inc.)  
10 on a 24-inch screen positioned 80 cm away from the participants. Before the main task,  
11 participants completed 6 practice trials with feedback and 32 practice trials without feedback.  
12 Written and visual instructions were provided prior to the practice trials.

13 During the main task, participants were required to achieve a minimum accuracy of 80%. On  
14 average, participants reached an accuracy rate of 95% in the main task block.

## 15 **2.5 Statistical analysis**

16 All analyses were conducted using R (version 4.2.2). A linear mixed model was calculated  
17 for each target variable, with data points clustered per participant by introducing participant  
18 intercepts as random effects. When applicable, items were also included as random effects.  
19 The fixed effects included in the model were TIME point, TREATMENT, the TREATMENT  
20 \* TIME interaction, and control variables (AGE, GENDER, BMI, RMSSD), along with  
21 exploratory three-way interactions involving potential mediators of the main TREATMENT  
22 \* TIME effect.

23 A model selection process was applied to each analysis, with predictors being consecutively  
24 added to the model. Likelihood Ratio Testing compared the goodness of fit of each model to  
25 the next simpler one, and predictors were retained if they improved the model's fit.

26 The main hypotheses were tested with TREATMENT \* TIME interactions in the respective  
27 model. The hypothesis was considered accepted if the interaction term was included in the  
28 final model, a significant predictor, and the effect aligned with the expected direction. Post-  
29 hoc comparisons and plots of the interaction effects were used to verify the expected  
30 direction of the effects.

31 As this study was a randomized controlled trial (RCT) with a waiting-list control group, the  
32 analyses included post-treatment data from the control group. Therefore, the post-treatment  
33 data points of the control group were classified into the post-treatment intervention group.

34 The same procedure was applied for reaction time data, involving three-way interactions  
35 instead of two-way interactions. These three-way interactions included TREATMENT,  
36 TIME, and FLANKER or CUE condition for the Executive and Orienting Network  
37 performance, respectively.

38

## 1 3 Results

### 2 3.1 Descriptive Statistics

3 Out of the 29 participants initially included in the study, 27 attended at least the first session  
4 and were included in the analyses. However, an additional 3 participants dropped out after the  
5 first and before the last session, resulting in 24 participants who completed the study entirely.  
6 Table 1 provides a description of the groups that underwent only the intervention and those  
7 who completed both the waitlist and intervention protocols.

### 8 3.2 Premenstrual Symptoms

9 Out of 21 PAF20 post values recorded for the T5 measurement, 9 were replaced with the  
10 follow-up measurements. This occurred because there was either no premenstrual phase  
11 during the intervention period or the premenstrual phase occurred during the first two weeks  
12 of the intervention phase.

13 The final model for predicting premenstrual symptoms incorporated the TREATMENT and  
14 TIME variables along with their interaction. Furthermore, it included the SCALE of the  
15 PAF20 questionnaire to which each symptom belonged (psychological vs. physiological  
16 symptoms) and its interaction with the TREATMENT \* TIME interaction (see Table 2). The  
17 final model was:

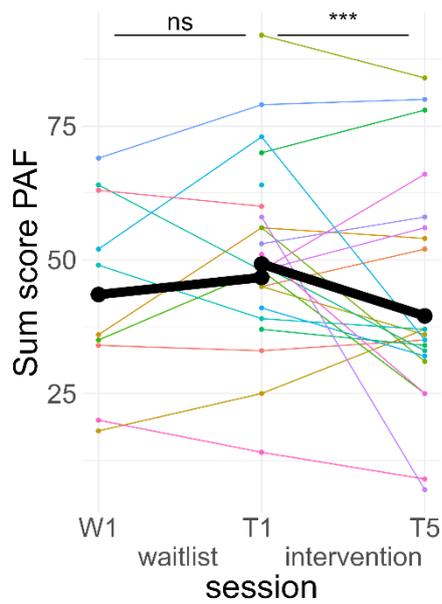
18  $\text{Value} \sim \text{treatment} * \text{time} + \text{scale} + \text{treatment}:\text{time}:\text{scale} + (1|\text{vpn}) + (1|\text{item})$ .

19 Post-hoc Tukey testing of the two-way interaction TREATMENT \* TIME revealed a  
20 significant improvement in the intervention group,  $d = -0.30$ ,  $t_{ratio}(1258) = -5.89$ ,  $p < .001$ ,  
21 whereas there was no significant pre-post difference in the waitlist group,  $d = 0.10$ ,  
22  $t_{ratio}(1252) = 1.35$ ,  $p = .18$  (see Figure 3). When SCALE was included in the interaction, it  
23 showed that the improvement in the intervention group was larger for psychological scale  
24 items ( $d_{psych} = -0.42$ ) than for physiological scale items ( $d_{physio} = -0.19$ ), with both  
25 improvements being significant. Detailed post-hoc testing results for the TIME \*  
26 TREATMENT \* SCALE interaction can be found in Table 3.

27

28

1 Figure 3. Course of premenstrual symptoms



2

3 Note. Colored lines indicate individual participants. Black lines indicate the predicted  
4 interaction effect based on the mixed effect model depicted in Table 2. The waitlist period  
5 occurred between sessions W1 and T1, while the heart rate variability biofeedback  
6 intervention period took place between T1 and T5. PAF – premenstrual assessment form;  
7 \*\*\* –  $p < .001$ ; ns – not significant.

1 **3.3 Depressive Symptoms**

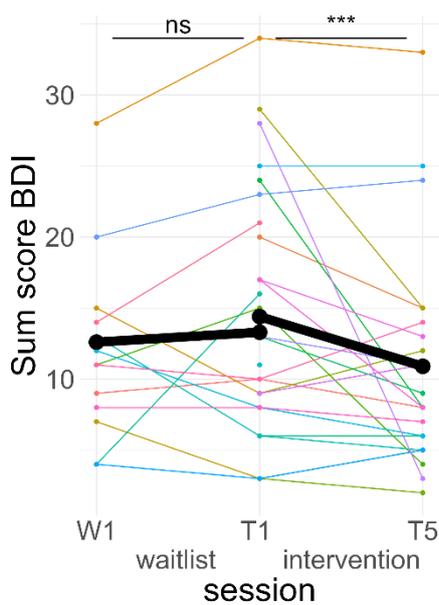
2 The final model predicting depressive symptoms included only TREATMENT and TIME, as  
3 well as their interaction as fixed effects (see Table 4). The model was the following:

4 Value ~ treatment\*time + (1|vpn) + (1|item).

5 A post-hoc Tukey test of the interaction showed that symptom scores significantly improved  
6 in the intervention period,  $d = -0.25$ ,  $t_{ratio}(1576) = -4.71$ ,  $p < .001$ , but not in the wait-list  
7 period,  $d = 0.05$ ,  $t_{ratio}(1567) = 0.73$ ,  $p = .46$  (see Figure 4).

8

9 Figure 4. Course of depressive symptoms



10

11 Note. Colored lines indicate individual participants. Black lines indicate the predicted  
12 interaction effect based on the mixed effect model depicted in Table 4. The waitlist period  
13 occurred between sessions W1 and T1, while the heart rate variability biofeedback  
14 intervention period took place between T1 and T5. BDI – Beck’s Depression Inventory II;  
15 \*\*\* –  $p < .001$ ; ns – not significant.

16

17

18

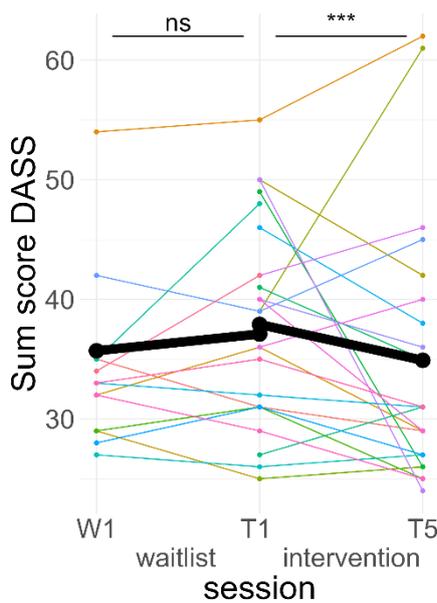
1 **3.4 Stress and Anxiety**

2 The best model predicting DASS values included the RMSSD and the DASS SCALE  
3 (anxiety, stress or depression) on top of TREATMENT, TIME and their interaction (see  
4 Table 5). There was no three-way interaction of TREATMENT \* TIME \* SCALE. The  
5 model was:

6  $Value \sim treatment*time + scale + RMSSD + (1|vpn) + (1|item).$

7 Post-hoc Tukey testing of the TREATMENT \* TIME interactions showed a significant  
8 improvement in the intervention period,  $d = -0.19$ ,  $t_{ratio}(1573) = -3.88$ ,  $p < .001$ , but not in the  
9 waitlist period,  $d = 0.09$ ,  $t_{ratio}(1567) = 1.37$ ,  $p = .17$  (see Figure 5).

10 Figure 5. Course of Anxiety/Stress symptoms



11

12 Note. Colored lines indicate individual participants. Black lines indicate the predicted  
13 interaction effect based on the mixed effect model depicted in Table 5. The waitlist period  
14 occurred between sessions W1 and T1, while the heart rate variability biofeedback  
15 intervention period took place between T1 and T5. DASS – Depression Anxiety and Stress  
16 Scales; \*\*\* –  $p < .001$ ; ns – not significant.

17

### 1 3.5 Heart rate variability

2 The RMSSD was log-transformed to approximate a normal distribution, aligning it with the  
3 methodology used in other vmHRV research studies. Two participants had to be excluded  
4 from the post measurement, as they had acute respiratory tract infections.

5 The final model predicting the log(RMSSD) included only TREATMENT, TIME and the  
6 TREATMENT \* TIME interaction as fixed effects (see Table 6).

7

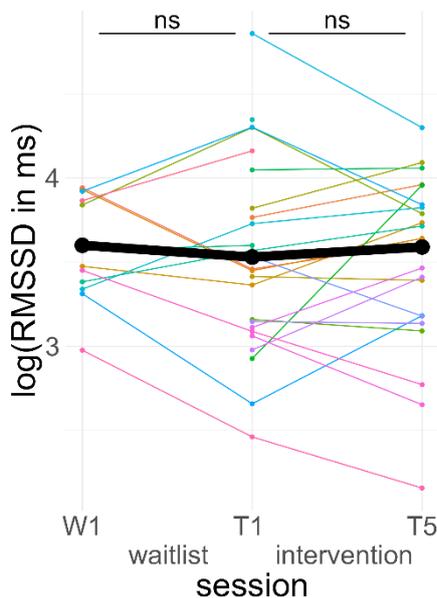
8 Value ~ treatment\*time + (1|vpn) + (1|item).

9

10 None of the fixed effects were significant predictors. A post-hoc Tukey test of the interaction  
11 confirmed no significant improvement in the intervention group,  $d = 0.11$ ,  $t_{ratio}(44) = 0.66$ ,  
12  $p = .51$ , and no significant pre-post difference in the waitlist group,  $d = -0.14$ ,  $t_{ratio}(43) = 0.61$ ,  
13  $p = .55$  (see Figure 6).

14

15 Figure 6. Course of vagally mediated heart rate variability



16

17 Note. Colored lines indicate individual participants. Black lines indicate the predicted  
18 interaction effect based on the mixed effect model depicted in Table 6. The waitlist period  
19 occurred between sessions W1 and T1, while the heart rate variability biofeedback  
20 intervention period took place between T1 and T5. RMSSD – root mean square of successive  
21 differences; ns – not significant.

22

23

### 1 3.6 Attentional control

2 The reaction time prediction model included main effects for TIME, TREATMENT, CUE,  
3 and FLANKER. Additionally, two three-way interactions were included – TREATMENT \*  
4 TIME \* CUE and TREATMENT \* TIME \* FLANKER. Both of these three-way interactions  
5 revealed significant terms in the model (see Table 7).

6

7 Reaction Time ~ treatment:time:cue + treatment:time:flanker + time + treatment

8 + cue + flanker + (1|vpn) + (1|item).

9

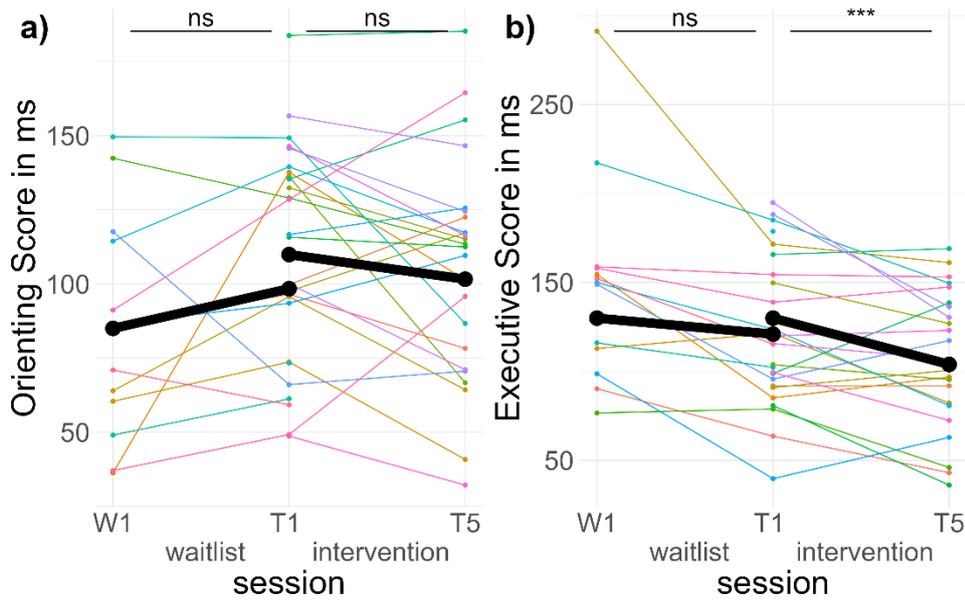
10 We used linear trend estimates from the emmeans package (v1.8.8) to compare valid vs.  
11 invalid (cue) and congruent vs. incongruent (flanker) slopes in each pre-post comparison.  
12 This approximated the original score calculations. Significant differences in slopes indicate  
13 changes in the Orienting Score (invalid vs. valid cue trials) or Executive Score (incongruent  
14 vs. congruent flanker trials) between pre and post-assessment.

15 In the TIME \* TREATMENT \* CUE interaction, there were no significant differences in pre-  
16 post slopes between valid and invalid trials during both the intervention period,  $d = -0.03$ ,  
17  $z_{ratio} = -0.67$ ,  $p = .91$ , and the waitlist period,  $d = 0.00$ ,  $z_{ratio} = 0.03$ ,  $p = 1$ , (see figure 7a).

18 In the TIME \* TREATMENT \* FLANKER interaction, there was a significant difference in  
19 pre-post slopes between congruent and incongruent trials during the intervention period,  $d = -$   
20  $0.18$ ,  $z_{ratio} = -4.60$ ,  $p < .001$ , but no difference in the waitlist period,  $d = -0.06$ ,  $z_{ratio} = -1.34$ ,  
21  $p = .54$ . The effect in the intervention period indicated less difference between valid and  
22 invalid trials post-treatment compared to pre-treatment, equivalent to better Executive Scores  
23 (see figure 7b).

24

1 Figure 7. Course of attentional control



2

3 Note. Colored lines indicate individual participants. Black lines indicate the predicted  
 4 interaction effect based on the mixed effect model depicted in Table 5. The waitlist period  
 5 occurred between sessions W1 and T1, while the heart rate variability biofeedback  
 6 intervention period took place between T1 and T5. a) Orienting Score – (reaction time  
 7 incongruent spatial cues - reaction time congruent spatial cues); b) Executive Score – (reaction time invalid  
 8 flankers - reaction time valid flankers). \*\*\* – p<.001; ns – not significant.

9

## 1 4 Discussion

2 In this study, we investigated the impact of a 4-week photoplethysmography smartphone-  
3 based HRVB intervention on premenstrual and depressive symptoms using a waitlist-control  
4 design. Additionally, we assessed its effects on stress symptoms, vmHRV, and attentional  
5 control. Our findings revealed improvements in premenstrual, depressive, and stress  
6 symptoms following the intervention, with no significant changes observed during the  
7 waitlist period. However, we did not observe any effects on vmHRV, and the results for  
8 attentional control were mixed.

9 The positive effects on premenstrual, depressive, anxiety, and stress symptoms found in our  
10 study highlight the feasibility and effectiveness of a smartphone-based HRVB intervention  
11 without the need for external devices. Laborde, Allen, Borges, Iskra, et al. (2022) reported  
12 similar effects of a slow-paced breathing intervention, whether or not visual feedback on  
13 current HRV was provided. This suggests that slow-paced breathing is the primary driver of  
14 the intervention's effectiveness. However, learning the technique of abdominal slow-paced  
15 breathing, which allows for a relaxed resonance frequency activation, can be challenging.  
16 The drastically slowed-down breathing can be uncomfortable and may even lead to  
17 hyperventilation (Szulczewski & Rynkiewicz, 2018). Providing visual feedback on  
18 respiratory sinus arrhythmia can assist users in correctly employing the method at home  
19 without extensive training. Moreover, this biofeedback feature can enhance user engagement  
20 with the app, as it offers immediate visual results of the breathing intervention, providing a  
21 sense of immediate gratification. Essentially, this form of feedback incorporates a simplified  
22 version of gamification into the intervention, which can increase motivation and engagement  
23 (Johnson et al., 2016).

24 Our primary objective was to investigate whether HRVB could help alleviate PMS  
25 symptoms. We observed a significant improvement in the premenstrual phase following 2-4  
26 weeks of HRVB practice compared to the preceding cycle in which no HRVB was practiced.  
27 The effect size we observed is approximately 0.3, with a slightly larger effect of 0.4 in the  
28 psychological symptom scale. In this context, the effect size is similar to the moderate effect  
29 size found in meta-analyses of depressive symptoms (Pizzoli et al., 2021). This finding  
30 supports the notion that PMS may result from an altered reactivity within the ALLO/GABA  
31 system (Hantsoo & Epperson, 2020), affecting the CAN as proposed by Thayer and Lane  
32 (2000). Consequently, interventions designed to target the interconnectivity and functional  
33 capacity of the CAN may hold promise in improving PMS symptoms.

34 However, further studies with expanded paradigms are needed to determine whether this  
35 effect is mediated by a reduction in stress throughout the menstrual cycle or by an increase in  
36 the capacity of the CAN, which may buffer modulatory fluctuations throughout the cycle. It  
37 also remains unclear whether there is a critical phase in the menstrual cycle when HRVB has  
38 a more significant impact on subsequent premenstrual symptoms. It is possible that practicing  
39 HRVB throughout the preceding follicular phase reduces chronic stress (Goessl et al., 2017)  
40 and, consequently, chronic ALLO exposure. This prolonged exposure has been suggested to  
41 contribute to atypical GABA receptor reactivity to ALLO fluctuations later in the cycle,  
42 which is assumed to cause PMS (Hantsoo & Epperson, 2020). Another possibility is that  
43 during the premenstrual phase, the acute stress-relieving effects (see e.g. Meier & Welch,  
44 2016; Prinsloo et al., 2013) of HRVB directly alleviate the symptom burden.

1 Independently of mechanisms of action, HRVB is an easily learned intervention with  
2 minimal to no side effects, offering PMS sufferers an opportunity to enhance their symptom  
3 management self-efficacy. Furthermore, it can lower the threshold for receiving treatment.  
4 When delivered through a smartphone application, it becomes even more accessible and, if its  
5 effectiveness is established, can be seamlessly integrated into widely used menstrual cycle-  
6 related health apps.

7 Our results also demonstrated improvements in depressive symptoms, as well as anxiety and  
8 stress symptoms, through the smartphone-based HRVB intervention. This aligns with prior  
9 research using other HRVB intervention methods (Goessl et al., 2017; Pizzoli et al., 2021),  
10 although the effects we observed are somewhat smaller than the meta-analytic effects on  
11 depression and anxiety/stress. This discrepancy may be due to ceiling effects. The majority of  
12 studies investigating HRVB effects typically focus on clinical populations with very high  
13 values in the respective outcome measures. Our inclusion criteria, on the other hand, involved  
14 individuals with above-average PMS symptoms or slightly elevated depressive symptoms.  
15 30% of the participants were included in our study due to only PMS symptoms. While  
16 clinically significant affective premenstrual symptoms (premenstrual dysphoric disorder) are  
17 often comorbid with anxiety and depression (Yonkers & McCunn, 2007), our subclinical  
18 sample likely had lower baseline scores in both BDI-II and DASS values compared to the  
19 samples in most studies included in the meta-analysis. This could account for the slightly  
20 smaller effect sizes observed in our study.

21 We did not observe improvements in vmHRV (RMSSD) following the HRVB intervention.  
22 Contrary to our findings, Laborde, Allen, Borges, Dosseville, et al. (2022) reported consistent  
23 elevations in vmHRV parameters after HRVB and slow-paced breathing interventions in their  
24 meta-analysis. The effect size for this improvement was approximately *Hedges' g* = 0.3.  
25 Notably, this effect size is smaller than the meta-analytic effect sizes for depressive  
26 symptoms (*g* = 0.4; Pizzoli et al., 2021) or anxiety/stress (*g* = 0.8; Goessl et al., 2017). These  
27 findings suggest that improvements in vmHRV alone do not fully account for the observed  
28 affective and cognitive effects. This is consistent with other findings that demonstrate  
29 physiological and clinical outcomes do not always change simultaneously in HRVB (Wheat  
30 & Larkin, 2010). Critically, our study may not have detected this effect due to its relatively  
31 small sample size. A G\*Power analysis indicates that a sample size of more than 70 would be  
32 required to replicate the effect of 0.3 with a power of .8. Our sample size was significantly  
33 below this threshold. The reason why effects were found in other outcome measures lies in  
34 the advantage of mixed model analysis, which allows us to include each item/trial  
35 individually without the need to condense the information into a composite score. This  
36 significantly increases the number of data points included, by 20 to 144 times, depending on  
37 the measurement. However, in the case of vmHRV, it is necessary compute a single value per  
38 measurement, which drastically reduces statistical power. This suggests the possibility that  
39 HRVB may have had a beneficial impact on vmHRV, but our study may have been  
40 underpowered to detect this effect.

41 The influence of the HRVB on the attentional control domains yielded mixed results. We  
42 chose to employ the Executive and Orienting Scores of the ANT-R as outcome measures,  
43 given their documented correlations with vmHRV (Blaser et al., 2023a; Quintana et al., 2017;  
44 Ramírez et al., 2015; Sørensen et al., 2019). Interestingly, despite previous studies (Quintana  
45 et al., 2017; Sørensen et al., 2019) indicating a stronger association between the Orienting  
46 Score and vmHRV (compared to the Executive Score vmHRV association), we did not

1 observe any improvements in this measure. However, we did find enhancements in the  
2 Executive Score following the intervention period. These varying outcomes align with the  
3 findings of a meta-analysis conducted by Tinello et al. (2022), who reported positive effects  
4 of HRVB on Executive Functions in approximately half of the studies they reviewed, with a  
5 slightly higher likelihood of effects in the attention domain. This highlights the need for  
6 further research to elucidate the specific impact of HRVB on cognitive outcomes.

7 Although we found significant beneficial effects of smartphone-based HRVB on several  
8 mental health and some cognitive outcomes, our study has several limitations that need to be  
9 considered. Firstly, the most notable limitation is our small sample size. Although linear  
10 mixed model analyses help to overcome the limited statistical power due to small samples by  
11 including individual items/trials in the analysis, it is important that the interpretation of the  
12 results and their applicability to larger populations must be considered with caution. Another  
13 limitation is related to the passive control group, which has methodological weaknesses. In  
14 future studies, it would be beneficial to implement active control groups to better distinguish  
15 the intervention's effects from any potential placebo effects. Additionally, we did not conduct  
16 clinical assessments of PMS or depression. However, it is essential to note that our study was  
17 not aimed at identifying treatments for a clinically relevant premenstrual dysphoric disorder.  
18 Instead, our primary focus was on investigating a user-friendly intervention to help  
19 individuals self-manage premenstrual symptoms, regardless of their severity levels.  
20 Furthermore, our study included participants regardless of their use of hormonal  
21 contraceptives and their current menstrual cycle phase. For future studies, it is advisable to  
22 standardize these criteria to ensure a more consistent assessment.

## 23 **5 Conclusion**

24 In summary, smartphone-based HRVB has proven to be effective in enhancing both  
25 emotional and cognitive well-being, without the need for external devices. This intervention  
26 holds promise as a novel approach for self-managing premenstrual symptoms and provides a  
27 more accessible solution for harnessing the known benefits of HRVB for depressive, stress,  
28 and anxiety symptoms, as well as certain aspects of attention.

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33 the Graduate Fund of the State of Brandenburg (Germany).

34 During the preparation of this work, the first author utilized ChatGPT 3.5 to enhance the  
35 text's readability. Prompts used were aimed at tasks such as "check grammar and spelling in  
36 this paragraph." After employing this tool/service, the author reviewed and edited the content  
37 as necessary and assumes full responsibility for the publication's content.

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40

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8

1 Table 1. Sample description

	Group waitlist		Group only intervention	
	(n = 13)		(n = 14)	
	Mean ± SD	Range	Mean ± SD	Range
Age	25.3 ± 7.0	18-37	22.6 ± 2.8	19-27
BMI in kg/m <sup>2</sup>	22.9 ± 4.5	18.3-32.2	22.9 ± 3.6	18.4-29.4
Gender	12f, 1m		14f	
Active menstrual cycle	11 yes, 2 no		14 yes	
HC usage	36.4%		42.9%	
PAF sum	54.7 ± 13.4	23-70	57.4 ± 20.2	19-93
BDI-II sum	12.9 ± 7.2	0-27	13.4 ± 8.0	2-30
Inclusion criterium	4 BDI, 4 PAF, 5 both		4 BDI, 4 PAF, 6 both	
DASS sum	34.1 ± 7,1	27-54	40.5 ± 8.3	25-50
RMSSD in ms	37.0 ± 10.9	19.6-51.5	41.9 ± 30.1	18.7-128.9
ANT-R Executive in ms	148.1 ± 56.8	76.7-291.3	129.2 ± 39.1	80.8-194.9
ANT-R Orienting in ms	85.0 ± 37.3	36.3-149.6	120.6 ± 35.1	46.7-183.8

2

3 Note. The DASS, RMSSD, and ANT-R values were obtained during the first laboratory  
 4 session of each participant. All other values were assessed during the screening. SD –  
 5 standard deviation; BMI – body-mass-index; HC – hormonal contraceptives; PAF –  
 6 premenstrual assessment form; BDI-II – Becks Depression Inventory; DASS – depression  
 7 anxiety stress scales; RMSSD – root mean square of successive differences; ANT-R – revised  
 8 attention network test.

9

Table 2. Results of a linear mixed model predicting premenstrual symptoms

<b>value PAF20 item</b>			
<i>Predictors</i>	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	2.92	2.44 – 3.40	<b>&lt;0.001</b>
group [W]	-0.28	-0.50 – -0.07	<b>0.010</b>
time	-0.30	-0.54 – -0.07	<b>0.012</b>
scale [psy]	1.08	0.61 – 1.56	<b>&lt;0.001</b>
group [W] * time	0.40	0.03 – 0.78	<b>0.034</b>
(group [I] * time) * scale [psy]	-0.36	-0.65 – -0.06	<b>0.017</b>
(group [W] * time) * scale [psy]	0.13	-0.26 – 0.51	0.520
<b>Random Effects</b>			
$\sigma^2$	1.40		
$\tau_{00}$ participant	0.58		
$\tau_{00}$ item	0.24		
ICC	0.37		
$N_{\text{participant}}$	24		
$N_{\text{item}}$	20		

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Observations 1300

Marginal  $R^2$  / Conditional  $R^2$  0.116 / 0.442

1

2 Note. The random effect structure includes participant intercepts and item intercepts. PAF20  
3 – premenstrual assessment form short version; group – treatment (biofeedback vs. waitlist);  
4 W – waitlist; I – intervention (biofeedback); psy – psychological symptoms.

5

1 Table 3. Post-Hoc Tukey effects of time\*treatment\*scale interaction term predicting  
 2 premenstrual symptoms

	Scale	Diff	<i>p</i>
Waitlist	Physio	0.06	.54
	Psych	0.14	.11
Intervention	Physio	-0.19	<b>.012</b>
	Psych	-0.42	<b>&lt;.0001</b>

3

4 Note. Diff – standardized pre-post treatment difference; psych – psychological symptoms;  
 5 physio – physiological symptoms.

6

Table 4. Results of a linear mixed model predicting depressive symptoms

<b>value BDI item</b>			
<i>Predictors</i>	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	1.69	0.54 – 0.83	<b>&lt;0.001</b>
group [W]	-0.09	-0.18 – 0.00	0.054
time	-0.17	-0.24 – -0.10	<b>&lt;0.001</b>
group [W] * time	0.21	0.09 – 0.33	<b>0.001</b>
<b>Random Effects</b>			
$\sigma^2$	0.34		
$\tau_{00}$ participant	0.10		
$\tau_{00}$ item	0.03		
ICC	0.27		
$N_{\text{participant}}$	27		
$N_{\text{item}}$	21		
Observations	1617		
Marginal $R^2$ / Conditional $R^2$	0.010 / 0.281		

1 Note. The random effect structure includes participant intercepts and item intercepts. BDI –  
2 Beck’s Depression Inventory II; group – treatment (biofeedback vs. waitlist); W – waitlist.

3

4

5

Table 5. Results of a linear mixed model predicting stress/anxiety symptoms

<i>Predictors</i>	<b>value DASS item</b>		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	1.12	0.64 – 1.60	<b>&lt;0.001</b>
time	-0.14	-0.22 – -0.07	<b>&lt;0.001</b>
group [W]	-0.11	-0.20 – -0.01	<b>0.023</b>
scale [D]	0.11	-0.19 – 0.40	0.466
scale [S]	0.44	0.15 – 0.74	<b>0.003</b>
rmssd	0.14	0.03 – 0.26	<b>0.015</b>
time * group [W]	0.21	0.09 – 0.34	<b>0.001</b>
<b>Random Effects</b>			
$\sigma^2$	0.35		
$\tau_{00}$ participant	0.14		
$\tau_{00}$ item	0.07		
ICC	0.39		
$N_{\text{participant}}$	27		
$N_{\text{item}}$	21		

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Observations 1617

Marginal  $R^2$  / Conditional  $R^2$  0.074 / 0.432

1

2 Note. The random effect structure includes participant intercepts and item intercepts. DASS –  
3 Depression Anxiety and Stress Scale; group – treatment (biofeedback vs. waitlist); W –  
4 waitlist; D – depression scale; S – stress scale; RMSSD – root mean square of successive  
5 differences.

6

7

1 Table 6. Results of a linear mixed model predicting vagally mediated heart rate variability

<b>log(RMSSD in ms)</b>			
<i>Predictors</i>	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	3.53	3.32 – 3.75	<0.001
group [W]	0.07	-0.15 – 0.29	0.546
time	0.06	-0.12 – 0.23	0.509
group [W] * time	-0.13	-0.42 – 0.16	0.381
<b>Random Effects</b>			
$\sigma^2$	0.08		
$\tau_{00}$ participant	0.21		
ICC	0.71		
N participant	25		
Observations	71		
Marginal R <sup>2</sup> / Conditional R <sup>2</sup>	0.003 / 0.711		

2

3 Note. The random effect structure includes participant intercepts. RMSSD – root mean square  
 4 of successive differences; group – treatment (biofeedback vs. waitlist); W – waitlist.

5

1 Table 7. Results of a linear mixed model predicting attentional control

<i>Predictors</i>	<b>Reaction time</b>		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	600.31	574.20 – 626.41	<0.001
time	-37.63	-49.22 – -26.05	<0.001
group [W]	39.00	31.02 – 46.99	<0.001
flanker [incongruent]	130.14	123.20 – 137.08	<0.001
cue [valid]	-98.44	-106.51 – -90.37	<0.001
time × group [I] × cue [invalid]	45.56	28.15 – 62.97	<0.001
time × group [W] × cue [invalid]	-0.22	-16.33 – 15.89	0.978
time × group [I] × cue [valid]	41.09	27.57 – 54.61	<0.001
time × group [I] × flanker [incongruent]	-26.57	-37.90 – -15.25	<0.001
time × group [W] × flanker [incongruent]	-9.44	-23.31 – 4.43	0.182
<b>Random Effects</b>			
$\sigma^2$	11369.21		
$\tau_{00}$ participant	4325.41		

ICC 0.28

N<sub>participant</sub> 27

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Observations 7040

Marginal R<sup>2</sup> / Conditional R<sup>2</sup> 0.267 / 0.469

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2 Note. The model predicts trial-based prediction times of the revised attention network test.  
3 The random effect structure includes participant intercepts. Group – treatment (biofeedback  
4 vs. waitlist); W – waitlist; I – intervention (biofeedback).

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